Evaluation of Geomembrane Destructive Seam Testing Frequencies and Risk Management

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ABSTRACT: An increasing demand for Construction Quality Assurance (CQA) for large landfill liner and final cover projects is being driven by three key recent trends: (1) the consolidation and closure of large Municipal Solid Waste (MSW) landfills; (2) the expansion and/or closure of large Coal Combustion Residual (CCR) landfills, and (3) the closure of large CCR surface impoundments. The unprecedented size of these emerging construction projects is cause to examine existing CQA practices and evaluate their projected efficacy for upcoming construction. Destructive seam testing for geomembranes deployed in the field is an area of particular interest because this kind of CQA testing has a direct impact on the quality, schedule, and cost of installations. This paper examines available probability-based quality assurance methods and considers their impact on risk of poor performance for large liner and final cover systems. Data from completed projects are used to illustrate the implementation of these methods and to simulate how a CQA program can manage risk.

INTRODUCTION

Renewed interest in the conduct of Construction Quality Assurance (CQA) for geomembrane installations is needed in order to resolve important risk management issues. Fortunately, large landfill liner and final cover projects in the Municipal Solid Waste (MSW) and Coal Combustion Residual (CCR) landfill sectors are facilitating the re-examination of CQA methods. Very large projects emphasize the implications of decisions regarding quality of work and acceptance of installation due to the magnitude of the consequences for poor performance. Accordingly, CQA decisions entail significant short-term cost and long-term liability trade-offs. Therefore, there is a need to tie testing practices and the resulting quality assurance decisions to actual measures of risk, which is not possible the way testing data are currently used.

In terms of traditional quality assurance engineering, the fundamental decision facing CQA Engineers is whether to accept or reject a geomembrane as installed. This decision has considerable financial, regulatory, and professional implications. This decision is complicated by the incremental nature of landfill construction work and the numerous variables affecting the quality of field seams. From quality assurance theory, there is an established notion of the concept of a lot – a fundamental unit of production to which this decision is applied. The quality assurance sampling schemes that are applied to the testing of these lots are designed to control the probability of accepting a lot with an unacceptable proportion of defective units. Ideally, a lot should have a controlled set of conditions such that all of its members can be considered together. In the practice of geomembrane seaming, this concept of a lot is difficult to implement since there are few clear demarcations in the project that offer boundaries to a lot. Also complicating the issue is that the acceptance or rejection of the seams must be made relatively quickly in order to facilitate the installation of additional liner system or cover system components. Therefore, in practice, the actual lot size that is being accepted or rejected is very small relative to the overall extents of the geomembrane installation.

Reliance on quality assurance services at landfills is very strong. The intuition of many quality assurance teams appears correct in that, under pressure to accept these very small lots, they are using multiple sources of information – not only destructive testing – to determine whether a lot should be accepted or rejected. Therefore, the basic statistical formulation of quality assurance sampling for acceptance has been confounded by actual practice. However, from a policy perspective, in the absence of high experienced inspectors (which is difficult to quantify and codify), how can a sampling program be designed so that some minimum level of assurance can be provided?

This paper examines available probability-based quality assurance methods and considers their impact on risk of poor performance for large liner and final cover systems. Seam strength is used to quantify seam quality in this instance, although it is recognized that there are other types of geomembrane defects that can lead to poor performance. Data from completed projects are used to illustrate the implementation of these methods and to simulate how a CQA program can manage risk. Questions addressed in the following sections include the following. Can we estimate the fraction of a lot that is defective without waiting until the end of the project? What available methods are better suited to address this problem? What are some useful variables for defining lots? Does an analysis of the example data support these recommendations?

GEOMEMBRANE SEAM TEST SAMPLING AND ACCEPTANCE

Ang and Tang (1975) identify two primary probability concepts used to develop sampling and testing schemes for quality assurance: sampling by attributes and sampling by variables. In accepting lots by attributes, a lot has a certain number of samples tested and classified as acceptable or defective. If a certain number of samples are deemed defective, the lot is rejected. Conversely, the lot is accepted. In acceptance sampling by variables, statistics are performed on the actual measured values to determine the likelihood that the lot does or does not meet the quality requirements. This approach requires fewer samples because more of the available information is used.

In quality assurance problems, two probabilities are of interest: producer's risk and consumer's risk. Producer's risk α is the probability that a lot with an acceptable fraction of defective units (alternatively, an acceptable value of some parameter) will be rejected. Consumer's risk β, is the probability that a lot with an unacceptable fraction of defective units (alternatively, an unacceptable value of some parameter) will be accepted. Since CQA inspectors represent the interests of the consumer, this paper focuses primarily on β.

In sampling by attributes, the probability of accepting a lot given a fraction of defective units p and n samples, r of which are deemed defective is expressed (Ang and Tang 1975):

$$g(p) \cong \sum_{x=0}^{r} \binom{n}{x} p^x q^{n-x} \quad (1)$$

where q = 1 – p and

$$\binom{n}{x} = \frac{n!}{x!(n-x)!} \quad (2)$$

is the binomial coefficient. Eq. 1 is known as the Operating Characteristic. Eq. 1 follows from a hypergeometric distribution, a type of discrete probability distribution. Eq. 1 is applicable to cases where the number of samples is small relative to the number of units in the lot. Since geomembrane seams are long continuous features and destructive samples are relatively short, comparably discrete features, this assumption is valid. For example, 10 standard coupons taken at a typical frequency of 1 per 150 m of seam represents 0.16% of the seam length. The Operating Characteristic can also be approximated using the Poisson distribution (GRI GM14):

$$g(p) \cong \frac{exp(-np)(np)^r}{r!} \quad (3)$$

Eq. 1 and Eq. 3 are applied to CQA problems by determining the number of samples n and maximum allowable defective samples r that satisfy target values of α and β.

In sampling by variables, test measurements are performed on n samples and a distribution (such as a normal distribution) is generated to approximate the distribution of the variable over the entire lot. Different statistical tests can then be applied. For example, for a given acceptable mean value of the measurement, the required number of samples and required minimum average test value (see "statistical value criteria" below) can be determined to provide target values of α and β for a CQA program. More readily applied to existing landfill CQA practice is the concept of the fraction defective criterion, similar to p in Eq. 1 and Eq. 3. In this case, the criterion is to reject a lot for which the estimated fraction of defective values, $\hat{p}$, in the distribution is greater than maximum allowable fraction M. In this case, n and M are calculated

$$n = \left[\frac{\Phi^{-1}(1-\beta) - \Phi^{-1}(\alpha)}{\Phi^{-1}(p_t) - \Phi^{-1}(p_a)}\right]^2 \qquad (4)$$

$$M = \Phi\left[\Phi^{-1}(p_a) - \frac{\Phi^{-1}(\alpha)}{\sqrt{n}}\right] \qquad (5)$$

where $\Phi(\cdot)$ is the cumulative standard normal function (N[0,1]), p_t is the maximum allowable fraction of defects (corresponding to β), and p_a is the acceptable fraction of defects (corresponding to α).

Inspection of Equations 1 through 5 reveals that the probability of accepting or rejecting a lot is dependent in part on the number of samples n taken from that lot for testing. In the context of quality assurance according to the probability concepts presented, it is important to emphasize that the entire lot is either accepted or rejected. Moreover, true rejection of a lot would mean its complete removal and replacement with product of acceptable quality. Since in landfill construction practice, it is not typical to wait until the completion of installation to determine whether or not to accept the installed geomembrane, lots cannot encompass the entire installation. Accordingly, for a responsive CQA sampling program, minimum acceptable values of n cannot equal the total samples obtained for the project. Therefore, careful consideration of the definition of a lot is needed.

In manufacturing, from which these concepts are drawn, a lot is a clearly defined production run that shares characteristics such as the production timeframe, materials, procedures, personnel, etc. In the context of a manufacturing facility, production lots can be sharply defined using one of these parameters and are readily distinguished from other lots. In contrast, there is not a consensus regarding the definition of a lot in the context of geomembrane field seaming. Should a lot correspond to an individual performing the work? A particular week or day of work? An area of coverage? Because of this ambiguity, statistics and test interpretations should be cautiously applied to field seams.

The existing literature offers some conventions for landfill CQA when applying quality assurance theory to geomembrane seam quality assurance. Richardson (1992) makes a distinction between methods to select the number of destructive samples n and methods to locate those samples. According to Richardson (1992), methods to select n include 1) Sample Density Method (i.e., 1 test per 150 meters of seam), 2) Error of Sampling method (e.g. ASTM E122), 3) Sequential Sampling (the number of samples is adjusted depending on the results). ASTM E122 addresses how to select a number of samples n to achieve a target value of certainty in the measurement, similar to the discussion for Equations 4 and 5. Daniel and Koerner (1993), GRI GM20, and GRI GM14 assume that destructive samples will be located according to fixed increment sampling and propose to adjust n by adjusting the size of the sampling increment.

Selecting locations to take samples in the field can follow several different strategies. Table 1 summarizes available sample location guidance for geomembrane seaming CQA. Similarly, several different acceptance criteria have been proposed. Table 2 summarizes these available criteria. Noteworthy from Table 2 is that most of the methods currently applied in practice are based on acceptance by attributes.

Table 1. Geomembrane Seam Sampling Strategies for CQA

Name	Description
100% sampling	Entire production lot is sampled. Applicable to non-destructive tests only (Richardson 1992)
Fixed Increment Sampling	Lot is divided into evenly-spaced sampling intervals (Daniel and Koerner 1993, Richardson 1992)
"Method of Attributes"	Fixed increment sampling is used up to an initial *n* value determined using an error of sampling method. Subsequent *n* values are adjusted depending on whether an acceptable number of "defective" measurements is exceeded or not (Daniel and Koerner 1993, GRI GM14) GRI GM14 provides recommendations for the acceptable number of "defective" measurements based on α.
Judgmental	The CQA inspector selects areas most likely to fail based on other observations or attempts to be random (Richardson 1992). Because additional information and bias is introduced, statistical inferences assuming random sampling cannot be applied.
Randomly Selected Sampling	A random number generator is used to select sampling locations according to a numbered grid (Daniel and Koerner 1993, Richardson 1992). Required in order to calculate accurate sample statistics and make inferences about the lot.
Stratified Random Sampling	Lots are divided into sub-lots with definable features. A random number generator is used to select sample locations (Richardson 1992)

Table 2. Geomembrane Seam Lot Acceptance Criteria

Name	Description
Statistical Value Criteria (sampling by variable)	Sample statistics such as mean and standard deviation must conform to specified criteria. Allows for a controlled number of "defective" measurements (Richardson 1992). Not typically applied in landfill CQA practice.
Maximum Number of Defects (sampling by attribute)	Similar to statistical value criteria. Establishes an allowable number of defective tests *r*. (Richardson 1992) Often applied in practice as a maximum proportion of test samples with failing results.
No defects (Maximum Number of Defects $r = 0$) (sampling by attribute)	Variant of maximum number of defects. Most readily understood criterion (Richardson 1992).
Control Charts (sampling by attribute)	Number of defective samples *r* are tracked separately according to a sub-lot, such as installer or day of work so that variations in measurements can be tracked to a particular cause. These control charts can be used to determine outliers and correct seaming procedures (Daniel and Koerner 1993, Richardson 1992, GRI GM20).

Of potential interest to landfill CQA, Ang and Tang (1975) describe a quality assurance method called Average Outgoing Quality (AOQ). In AOQ, lots are either accepted or rejected based on an initial sampling. Rejected lots are screened completely for defective units and returned with no defective units. At first, this scheme may appear similar to the common geomembrane industry practice of "tracking" failed destructive tests to points along a field seam where passing results are obtained and then replacing the seam in between. However, since only the failed sample is replaced, this method does not address all of the potential defective seams elsewhere in the lot. Therefore, this approach does not fundamentally alter the probability of accepting lots with unacceptable fractions of defective seams. Accordingly, only the initial samples are considered reliable for purposes of estimating the fraction of defective seams in the lot. Destructive samples that are located to "track" a failing test are necessarily excluded from a statistical analysis of the lot. This convention is applied in the analysis that follows.

EXAMPLE GEOMEMBRANE INSTALLATION DATA

To illustrate the interaction of the various proposed sampling strategies and acceptance criteria with collected field data, a relatively large destructive test database was selected. The example database was selected from Site A, a 50-hectare (120-acre) double-lined pond. The destructive seam test log from the primary geomembrane installation, consisting of 505 sets of destructive tests, is used in the following calculations and discussion. This data set includes 430 samples from fusion welds, 365 of which are initial destructive samples. In order to provide a complete example, only the fusion seam test data is used below. However, it should be noted that the typically lower-quality extrusion seams present a persistent quality problem. The fusion seam destructive test samples were tested according to the criteria in Table 3.

At the time CQA services were performed for Site A, a combination of fixed increment and judgmental sampling was used to locate samples. Acceptance of the primary geomembrane installation was based on a maximum number of defects criterion as well as correction of seams determined to be deficient based on visual inspection. Table 4 summarizes the results of the testing program for all fusion welders (total installation) and for 8 of the welders with the greatest number of samples (8 lots).

For reasons that will be discussed below, a division of the fusion seam testing data set into lots according to welder will be pursued. In practice, it is equally if not more likely that division of the data into lots by day or week, type of material, location of seam, etc. will be more useful for routine acceptance of installed seams. In either case, because both environmental conditions and welder are variables with direct influence on quality, they are relevant variables to use when defining the limits of lots.

Table 4 indicates that the total number of failed initial destructive samples is 19 out of a total of 365 samples. 365 samples is a sufficiently large sample set that the fraction 19/365 = 5.2% is a good estimate of the fraction of total installed seam that does not meet the criteria in Table 3. In other words, if the entire length of installed seam were cut into destructive samples, 5.2% of the samples is expected to not meet the Table 3 criteria. This result is readily obtained considering the data at the end of installation. However, it is highly undesirable to make a determination to accept the entire 50-hectare installation in one lot. Accordingly, additional acceptance criteria and sampling strategies will be evaluated that allow the consideration of smaller lots.

Table 3. Passing Destructive Test Criteria for Fusion Seams at Site A

	4 of 5 tests	1 of 5 tests
Peel Strength (5 tests each side for 10 total)	≥ 429 N/25 mm (98 lb/in)	≥ 346 N/25 mm (79 lb/in)
Shear Strength	≥ 530 N/25 mm (121 lb/in)	≥ 425 N/25 mm (97 lb/in)

Table 4. Summary of Destructive Seam Testing For Site A Primary Geomembrane (Initial Samples Only)

		Failures			
Welder	**Samples**	**Lab Shear**	**Lab Peel**	**Field**	**Total**
all	365	1	7	11	19
A	43	0	0	1	1
B	14	0	0	0	0
C	65	1	0	1	2
D	50	0	2	5	7
E	89	0	0	1	1
F	43	0	2	1	3
G	22	0	1	1	2
H	14	0	2	0	2

First, applying sampling by attributes, Eq. 1 can be used to determine the minimum number of samples n required to accept a lot while meeting target values of α and β. This approach is also used by GRI GM14 to adjust the sampling interval according to the notion that accepting a lot results in a constant or increased sampling interval while rejecting a lot results in a reduced sampling interval.

Assuming that a fraction of failing seam p = 5% is acceptable and that β = 5% is desired (a 5% probability of accepting a lot with p > 5%), solving Eq. 1 by trial and error yields n = 93 and r = 1. For α = 5%, n = 93, and r = 1, Eq. 1 yields p = 0.4% (a 95% probability of accepting a lot with p > 0.4%). Hence, in order to assure with 90% confidence that the overall fraction of welded seam that is defective is between 0.4% and 5%, 93 samples are required, a maximum of 1 of which are allowed to fail. Noting the values in Table 4, n = 93 is a quarter of the total initial samples. It is also greater than all of the sample sets defined by any one welder. Therefore, acceptance criteria based on sampling by attributes theory are unable to deliver the target level of confidence without excessively large numbers of samples. Alternative compromises to use sampling by attributes include a reduced level of confidence or the possibility of rejecting large lots. An alternative approach implementing sampling by variable is illustrated as follows.

Next, applying the above criteria using sampling by variable, the corresponding number of required samples is less to achieve the equivalent level of confidence. Following the previous example, α = 5%, β = 5%, p_a = 0.4%, and p_t = 5%. Substituting into Equations 4 and 5, n = 10.7 and M = 0.0158. Therefore, using acceptance by variable, 10 to 11 samples are required, producing a distribution suggesting a maximum fraction of 1.58% seam that is defective. These values can be achieved with the existing data set. The following calculations explore how the results of the sample tests can be interpreted according to the distribution of the measured values.

An initial consideration of the statistics resulting from this data set is how to treat individual strength measurements when estimating the defective fraction of the entire lot. According to Table 4, only 1 of the 19 failures resulted from a low shear strength value measured in the lab. Additionally, only lab-measured strength values were recorded and available to this study. Therefore, this analysis focuses on peel strength. FIG. 1 presents a histogram of lab-measured peel strength values. All individual test measurements are reported in this figure (i.e., all 10 of the peel strength measurements are included from each sample). The statistics for this data are sample mean = 555 N/25 mm and sample standard deviation = 40.8 N/25 mm. Considering the distribution in FIG. 1 as a normal distribution, the fraction of all seam peel strength values expected less than 429 N/25 mm is 0.0991%. Accordingly, the probability of obtaining at least 1 peel strength value less than 429 N/25 mm from 10 random measurements ($P_{min,10}$) is approximated

$$P_{min,10}(< 429N/25\ mm) = 1 - (1 - 0.000991)^{10} = 0.00986 \qquad (6)$$

The corresponding number of expected defective samples from a total of 365 tests = 0.00986 × 365 = 3.6 failing samples. This number is significantly less than the observed number of 19 defective samples. It is undoubtedly affected by the omission of test results from samples failing during field testing. However, it is also affected by the correlation of measurements taken from the same sample (i.e., intra-sample test distributions are not representative of inter-sample distributions). Therefore, FIG. 2 shows the distribution of minimum peel strength values recorded for all lab-measured Site A samples. The statistics for this data are sample mean = 504 N/25 mm and sample standard deviation = 39.2 N/25 mm. Accordingly, using this distribution, $P_{min,10}$(< 429 N/25 mm) equals the fraction of the distribution < 429 N/25 mm = 0.02778, yielding an expected number of defective samples = 0.02778 × 365 = 10.1. This value is also affected by the omission of field test failures, but notably appears to better match the final results. The distribution of minimum test values is used in the following evaluations.

Following from the n = 10.7 and M = 0.0158 sampling criteria established above, Table 5 presents the statistics from the first 10 samples from each lot defined in Table 4. Noteworthy results in Table 5 include the ability of this sampling program to calculate fraction failing values close to those ultimately computed for the entire sample set. This result is particularly noteworthy considering that, except for welders D and G, no actual failures had yet been produced in the first 10 samples. With the inclusion of measurements from the failing samples, the correlation between expected and actual total failed samples improves for each lot. The expected failures for the all-welders lot is much different than measured, highlighting that the division of lots by welder is more sensible than ignoring this variable.

In order to further explore the notion of a limited initial sample set, Table 6 presents the statistics from the first 5 samples from each lot. The expected number of failures from this sample group also shows good correlation with the value ultimately measured for the entire lot.

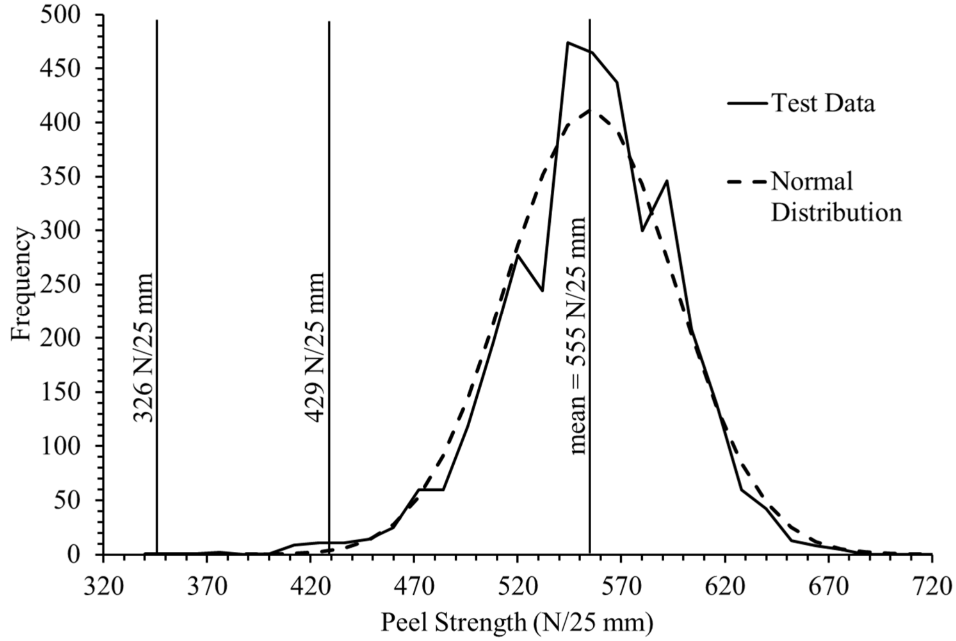

FIG. 1. Histogram of all Collected Peel Strength Data for Site A – All Tests

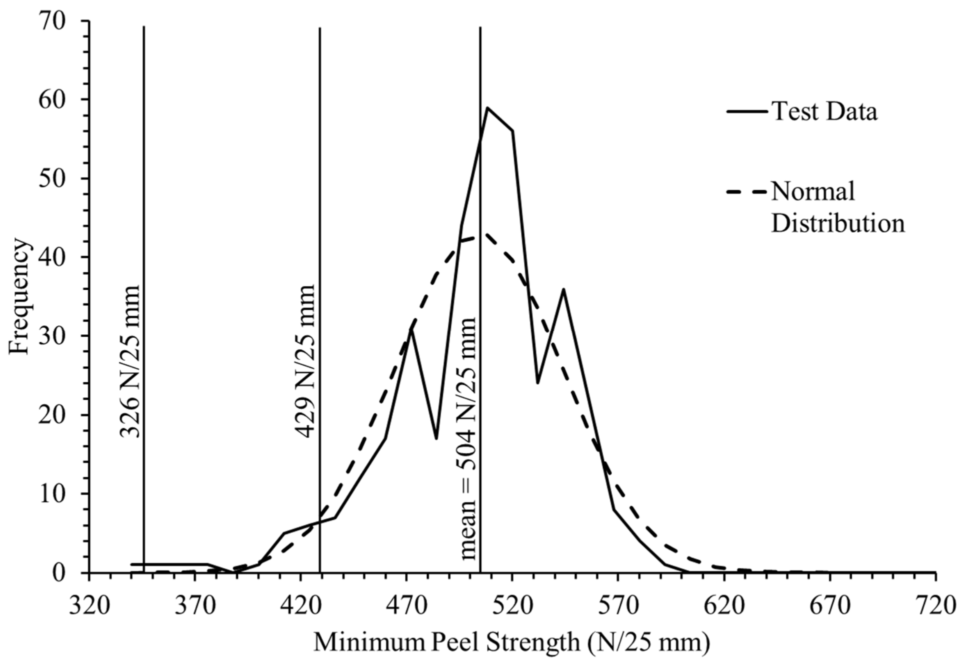

FIG. 2. Histogram of all Collected Peel Strength Data for Site A – Min. Values

Table 5. Peel Strength Testing – Min. Test Values for First 10 Samples

welder	samples	tests	Average (N/ 25 mm)	std. dev. (N/ 25 mm)	frac. < 429 N/25 mm	expected failures	actual failures
all	10	10	488	53.1	13.45%	49.09	19
A	10	10	501	26.4	0.33%	0.14	1
B	10	10	508	34.6	1.09%	0.15	0
C	10	10	505	42.3	3.68%	2.39	2
D	10	9*	495	18.0	0.01%	0.01*	7
E	10	10	508	33.1	0.87%	0.77	1
F	10	10	512	44.8	3.23%	1.39	3
G	10	9	476	28.5	4.89%	1.08	2
H	10	10	484	75.3	23.35%	3.27	2

*note: expected failures = 2.52 when 400 N/25 mm substituted for missing test

Table 6. Peel Strength Testing – Min. Test Values for First 5 Samples

welder	samples	tests	Average (N/ 25 mm)	std. dev. (N/ 25 mm)	frac. < 429 N/25 mm	expected failures	actual failures
all	5	5	503	52.8	8.19%	29.88	19
A	5	5	496	28.3	0.93%	0.40	1
B	5	5	504	39.5	2.81%	0.39	0
C	5	5	503	58.1	9.99%	6.49	2
D	5	4*	499	23.4	0.14%	0.07*	7
E	5	5	489	29.1	2.04%	1.82	1
F	5	5	489	42.6	7.79%	3.35	3
G	5	5	481	37.3	8.30%	1.83	2
H	5	5	504	74.5	15.58%	2.18	2

*note: expected failures = 7.56 when 400 N/25 mm substituted for missing test

DISCUSSION

This paper presented a brief summary of probability-based quality assurance theories applicable to geomembrane seaming CQA. Based on a review of typical CQA guidance and reflecting on typical industry practices, there is a significant difference between the sampling and acceptance criteria theory and how CQA practice is generally conducted. General quality assurance philosophy is to limit the probability of unacceptable quality to a predetermined value. In contrast, the philosophy of many CQA firms in practice is to detect as many defects as possible.

Moreover, since CQA inspectors routinely accept seams on a nearly continuous basis, the explicit definition of lot would appear to be very small for geomembrane seams relative to the number of destructive samples. This situation has resulted in CQA inspectors correctly applying the intuition that additional observations are necessary to assure quality for these relatively small lots. In the case of experienced inspectors skilled at visually recognizing variables leading to poor-quality seams, this intuition results in the "judgmental" (Table 1) location of destructive samples and a general bias to overestimate failures, which is conservative from a consumer's risk perspective. However, from a policy perspective, CQA plans and regulations should not be formulated around such non-specific notions.

Accordingly, the goal for regulatory policy and CQA plans should be to establish a baseline set of sampling practices and minimum performance targets based on probability principles. In the formulation of this policy, it is highly desirable that unnecessary destructive samples be avoided in order to limit damage to the geomembrane while still performing sufficient sampling to assure quality. At the same time, there is an on-going need in industry to qualify relatively small lots in the course of construction. In order to meet all of these needs, this paper explored the possible implementation of an acceptance-by-variable-based sampling methodology. The Site A example presented in the previous section illustrated how this approach can deliver superior confidence with fewer samples than the competing acceptance-by-attribute-based methodologies. Particularly noteworthy is the fact that this methodology can be adopted utilizing existing practices for the inspection of seams, collection of samples, and measurement of test values. Additional tests and measurements are not added.

Some potential problems with acceptance by variable for destructive testing include 1) the fact that failures are produced by multiple modes, not just shear or peel strength, 2) in current practice, lab testing is not typically continued after a failure determination is made, making reliable statistics difficult with current data sets, 3) field test results are typically not recorded, excluding variables from the record. Many of these problems can be rectified by more comprehensive record keeping.

Regarding lot definition, because there are many conditions that vary over time, selecting the entire project as the lot size does not confirm practitioners' intuition. As an extreme example, to achieve the same level of confidence for 5-hectare project that lasts a few weeks, a random sampling strategy would require the same number of samples as a 50-hectare project lasting ten times as long. Therefore, a recognition of these other conditions is needed.

Because a statistical consideration of the actual production units is the only completely valid way to control for the quality of the produced product, this paper has not considered destructive tests on trial welds, start-up welds, or other similar non-production samples where the seamer knows in advance that the weld will be submitted for testing. From a statistical perspective, such a sampling scheme is not random and therefore completely biased. From a practical perspective, it can be expected that seamers will produce higher-than-average quality welds when they know in advance where the test will be performed. For these reasons, trial welds cannot be relied upon for lot acceptance. Trial welds are therefore mostly useful as an aid to the installer to practice welding and deduce the proper operating parameters for production welding given environmental conditions.

CONCLUSIONS

A brief review of relevant quality assurance theory and existing CQA practices with respect to destructive geomembrane seam sampling and lot acceptance was presented. Following from this review, the selected theory was applied to an analysis of an existing destructive test database. The results of this analysis illustrated the potential for acceptance-by-variable methodologies to be successfully applied in geomembrane

CQA practice. This approach appears particularly well-suited to resolving questions about seam quality with relatively few samples, allowing corrective action to be applied earlier during installation, increasing reliability and decreasing construction delays. This approach is further enhanced by observations external to destructive testing that reduce the risk of defects more.

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